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INTELLIGENT VEHICLE INSPECTION TOOL DESIGN BASED ON FREEMAN CHAIN CODE FOR AUTOMATIC ANNOTATION OF 3D MODELS

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Abstract. Autonomous vehicle are more and more widely used in daily life, and the requirements for their safety performance are higher and higher. As a tool for testing auto parts, intelligent inspection tools are crucial to the guarantee of automobile quality. However, traditional fixture design relies on manual drawing, which is inefficient and prone to errors. To solve this problem, this research uses Freeman chain code to determine the annotation object, uses case clustering method to annotate, and uses error back propagation algorithm to realize case knowledge classification learning, and designs intelligent vehicle inspection tool design technology based on Freeman chain code 3D automatic annotation method. The experimental results show that the geometric feature matching results are correct, and the difference in feature comparison results is significant, with a high accuracy rate. Meanwhile, the geometric similarity annotation method has a high accuracy rate, taking only 3 minutes to complete the annotation, which is 7 minutes longer than traditional manual annotation. The error backpropagation algorithm can accurately achieve feature classification, and the design time of size chain inspection tool deformation design is reduced by 214min compared to manual reverse deformation design, significantly improving design efficiency. In summary, the proposed design method for automotive inspection tools can achieve automatic model annotation, improve design efficiency, and reduce design time.

Key words: Automatic Annotation; Freeman Chain Code; Bp Neural Network; Inspection Fixture Structure;

1. Introduction. In recent years, with the boost of intelligent vehicles, their safety and reliability have become hot topics of concern. The continuous development of the automotive industry has led to increasing attention being paid to the design of automotive inspection tools. Automotive inspection tools are tools used to detect the size, shape, and quality of automotive components, playing a crucial role in the quality and production efficiency of automobiles. The use of high-quality automotive inspection tools can greatly improve production efficiency, reduce product defect rates and production costs [4]. The design of intelligent vehicle inspection tools is an essential method for enhancing the efficiency of automobile manufacturing. Therefore, this study uses Freeman chain codes to automatically annotate lightweight models, and combines the Model based Definition (MBD) model and Back Propagation (BP) algorithm to achieve similarity retrieval. Therefore, it is redesigned based on existing inspection tool cases. Propose an intelligent vehicle inspection tool design scheme based on Freeman chain code for automatic annotation of 3D models (3DM). The innovation points of the research mainly include two points: firstly, using Freeman chain codes for searching and matching geometric features (GF) for determining annotation objects, and proposing an automatic annotation method for geometric similarity; The second is for utilizing BP neural network (NN) algorithm for learning and classifying MBD model knowledge, and propose a similarity retrieval method based on MBD model. The research structure is separated into four. The first is a review of related outcomes; The second proposes a design technology for intelligent vehicle inspection tools based on geometric similarity features and BP NN algorithm, which automatically annotates 3DM using Freeman chain codes; The third is the validation of the design scheme presented by the research institute; The final is a relevant summary.

2. Related work. As the boost of natural language processing technology, automatic annotation technology has been widely used in text classification, entity recognition, automobile manufacturing and other fields. Chen et al. proposed an automatic data labeling pipeline for 3D LiDAR data for solvingthe problem of segmenting moving objects in the environment. The experiment illustrates that this method can markedly label LiDAR data and generate labels in different outdoor environments [5]. Mahajan V et al. proposed a machine learning

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model based on automatic labeling and deep learning to predict lane change maneuvers in order to solve the problem that maneuver prediction needs to deal with large labeled datasets. The classification results show that real-time prediction of lane changes can be predicted efficiently, with an average The detection time is at least 3s, and the proportion of false positives is very small [6]. Liu et al. proposed an automatic annotation method (AAM) of hybrid atlas forest model in view of spatial index to meet the problem of accurately registering all atlases to the target image. The outcomes illustrate that this method diminish the dependence on precise registration and improves annotation [7]. Elhousni M et al. proposed a method that can automatically label high-definition maps from raw sensor data to address the issue of errors in creating high-definition maps. The outcomes indicate that the presented method can generate high-precision high-definition maps, accelerating the process of constructing and labeling high-definition maps [4]. Guerra et al. proposed a speech corpus automatic annotation scheme to monitor the dynamic changes of Mel frequency related cepstrum vectors that make up book codes. The results indicate that the correct labeling percentage of this scheme is 97.9%, and the time taken is significantly less than that of manual labeling [9].

With the arrival of the big data era, classification and retrieval technology has been widely applied as a method of information classification and retrieval. Cheng Q et al. presented a rapid design method for process equipment in view of 3DM MBD classification retrieval for changing the relevant method for enhancing design efficiency. This test shows that this method shortens the development cycle of the device and can help users produce 3DM of complex products [3]. Ebadi N and others proposed a practical two-stage attitude detection model to address the issue of lack of compatibility in the fact verification process due to human modification of classification models. The outcomes indicate that the average weighted accuracy is 82.1, which can accurately distinguish between false news and real news headlines [11]. Rosewelt et al. proposed a relevant data retrieval model based on semantic analysis to overcome the unreasonable accuracy of existing models. The outcomes indicated that the data retrieval process of the model was effective, and the identified dataset showed good test results [12]. Rashid A M et al. proposed a scheme for retrieving images in smart cities using grayscale co-occurrence matrices to reduce search time for image content. The experimental results showed an average accuracy of 6.6 and an average recall rate of 3 [13]. Alrahhal M et al. proposed a COVID-19 diagnostic system using medical image classification and retrieval in order to provide a detection method that mainly relies on artificial intelligence and radiographic image analysis to determine disease infection. The experimental results proved the effectiveness of the proposed system , with 100% accuracy in classifying input images as X-ray or CT scans, 99.18% accuracy in classifying X-ray images as COVID-99 or NOTCOVID-18, and 99.18% accuracy in classifying CT scans as COVID-97 or NOTCOVID-84 It is 97.84% [14].

In summary, a large number of scholars all over the world have conducted study about the application of automatic annotation technology and classification retrieval technology from multiple aspects at present. However, there has not been in-depth research on the design of automatic annotation of 3DM for automotive inspection tools. Therefore, the study adopts Freeman chain code to achieve automatic annotation of lightweight models, and combines MBD model and BP NN algorithm to achieve similarity retrieval. A smart car inspection tool design scheme based on Freeman chain code for 3DM AAM is proposed.

3. Design of Intelligent Automobile Gauge Based on Automatic Labeling of 3D Model. With the boost of the automotive market, the current design method of automotive inspection tools seriously restricts the production efficiency of automobiles. In order to solve the problems of low efficiency and error-prone manual drawing in traditional gage design, this study proposes an intelligent automotive inspection tool design technology based on the Freeman chain code based 3DM AAM. This technology first determines the annotation object using GF through Freeman chain codes and the longest Gongzi sequence, and then checks and optimizes the annotation results through clustering annotation. Then, BP NN algorithm is used to classify information like geometric dimensions, features, and processes, optimizing the retrieval and application of similar cases.

3.1. Intelligent Design and System Framework of Automobile Inspection Tools. The boost of the automotive manufacturing industry not only requires continuous improvement in product quality, structural design, and processing methods, but also puts forward stricter requirements for the design of inspection fixture structures [15]. At present, traditional inspection tools are difficult to meet the requirements of rapid automobile manufacturing, which has a serious impact on its production efficiency. Automobile inspection tools are responsible for detecting whether automotive parts are qualified and ensuring the quality of parts,

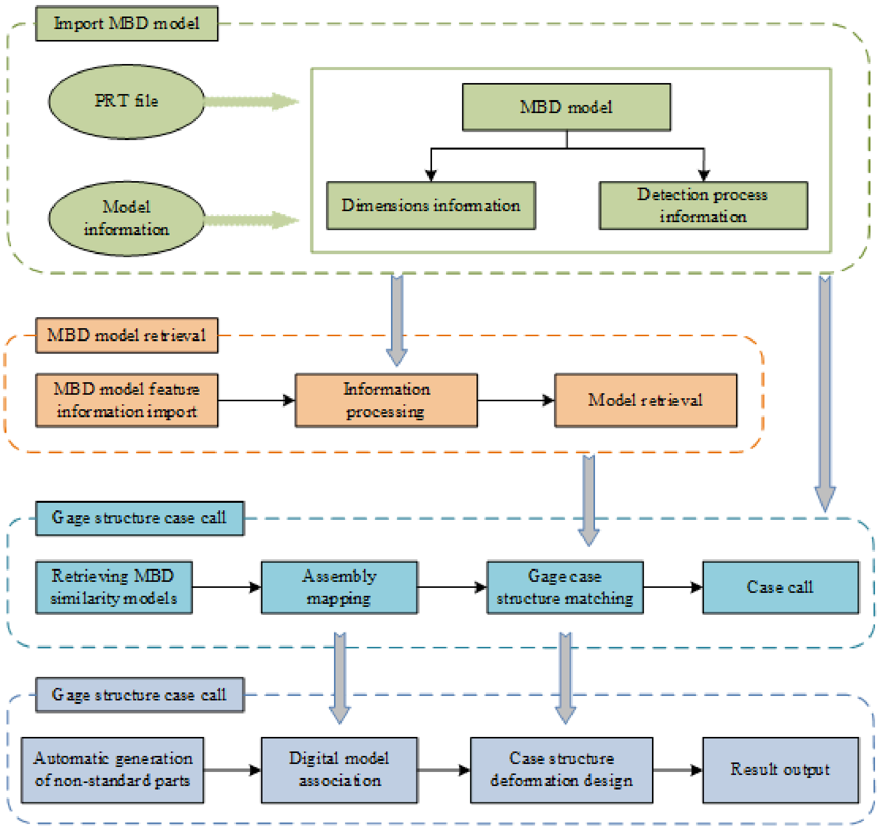


Fig. 3.1: Inspection tool design system process

and occupy an important position in the automotive manufacturing industry [16]. Automotive inspection tools possess an essential influence on the automotive production. During the product stage, the structure and size of automotive parts can be optimized. During the product validation stage, the design results of the parts can be verified in a real assembly environment. During the planned production stage, the reason why the quality of automotive parts cannot meet the assembly requirements can be determined. The specific process of designing a car inspection system is shown in Fig 3.1.

Fig 3.1 demonstrates that the checking tool system is mainly composed of four modules: importing model parts, parts retrieval, Anli model calling and checking tool case deformation design. the study first utilizes 3D annotation technology to automatically annotate lightweight models and generate MBD models. MBD models are a method of defining individual parts and product assemblies using 3D models (such as solid models), product and manufacturing information, and associated metadata. Then, the part feature information in the MBD model is extracted and transformed into vector form for similarity retrieval. Next, the mapping relation in the MBD model and the fixture is linked, and the fixture case structure model is used for operation. Finally, the design results are exported and saved through deformation design. To address the issues of long cycle time and low efficiency in designing new products, this study further utilizes a searcher with similarity retrieval function to provide engineers with similar design cases for reference. However, the case model requires modular replacement and modification to meet the requirements of new product inspection fixture design. Therefore, the above system has been improved to an intelligent design system for automotive inspection fixtures in view of the MBD model. The system mainly includes four parts: interface layer, functional layer, data layer, and support layer. The interface layer is the operation interface for the designer to design the gage. The function

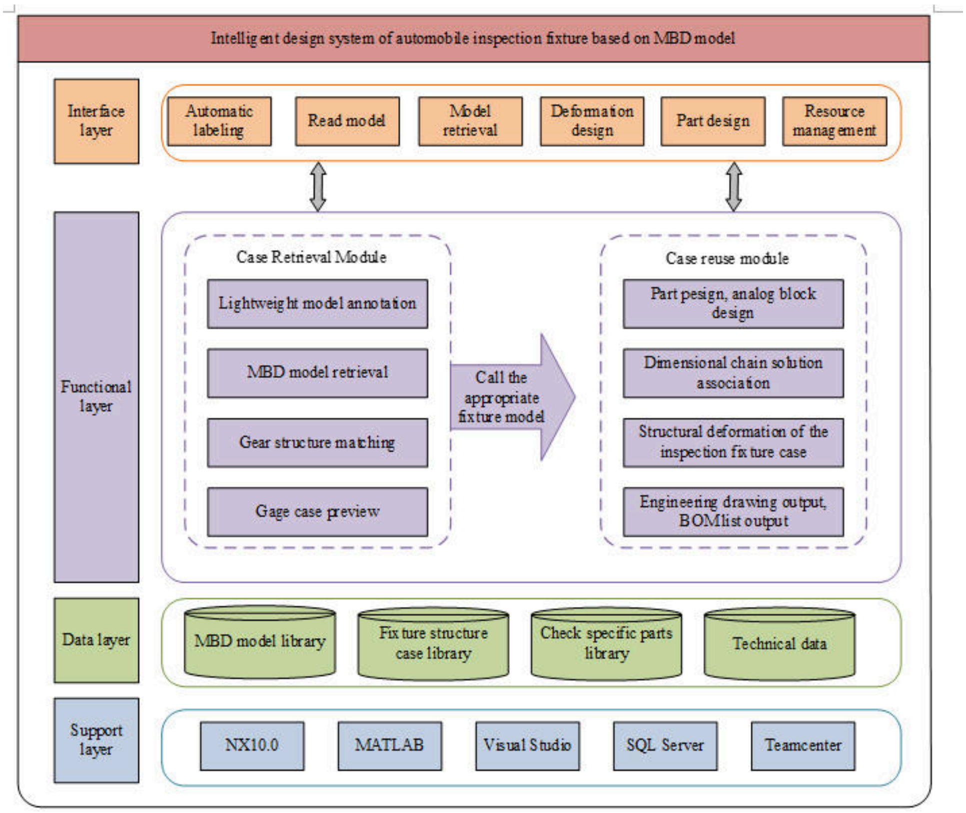


Fig. 3.2: System framework

layer is the place for data interaction between gage model retrieval and case reuse. The data layer is When using the system to develop inspection tools, the design resources are managed, and the support layer is to provide technical support for the system. The specific system framework is shown in Fig 3.2.

Fig 3.2 indicates that the system adopts a forward design method, using C as the system design language, and integrates the Microsoft Visual Studio2021 platform into MATLAB for secondary development of the NX design platform. Meanwhile, it utilizes the SQL Server platform to store and read/write the data case library, thereby creating a rapid design system for inspection tools based on MBD model similarity retrieval, and completing the construction of the inspection tool design platform. The inspection tool design platform mainly includes four functional interfaces: automatic annotation, retrieval, deformation design, and design result output. Among them, the automatic labeling function is to realize the automatic labeling of the entire MBD model, and the MBD model retrieval function is to realize the matching of similar cases. Provide design support for calling the configuration link. The deformation design function is to modify the searched similar cases to meet the new inspection fixture structure design, and the design result storage and output function is to output and save the obtained inspection specific engineering drawings. Automatic annotation is achieved using Freeman chain codes and Longest Common Subsequence (LCS) similar GF retrieval matching methods [17]. The MBD model retrieval function includes three steps: reading MBD model data, case description and calling the fixture structure corresponding to similar MBD models. The deformation design function uses the bill of materials (BOM) assembly structure for case deformation correction, and the design result output function uses the Product Data Management (PDM) system to output the generated engineering drawings and save the design results. The inspection fixture design platform integrates various peripheral interfaces such as serial port, CAN bus interface, AD/DA interface, SD/MMC card reader and DEBUG debugging interface. Function processing includes serial port initialization, Modbus frame analysis, Modbus frame structure and various services Processing and other functions. In summary, the construction of the inspection tool design system has been completed.

3.2. Design of Automatic Annotation Method for 3DM Based on Freeman Chain Codes. In the process of product design for inspection tools, manual image recognition takes a long time and the accuracy is not high. Therefore, for enhancing the staff image reading and reducing product design time, this study presented a 3DM AAM in view of Freeman chain codes [18]. The research uses Freeman chain code to describe the contour information of the geometric image, and uses LSC to retrieve and match the geometric features to determine the labeling object, omitting the step of manually identifying the geometric features of the image to determine the labeling object. Freeman chain code is a method of describing a curve or a boundary by using the coordinates of the starting point of the curve and the direction code of the boundary point. It is often used to represent curves and area boundaries in the fields of image processing, computer graphics, and pattern recognition. Freeman chain codes are used to describe the contour lines of objects or shapes and their geometric features. By assigning a unique number to each point on the contour, a sequence composed of numbers can be generated, which can be expressed as a sequence with different rotations. The only form of transgender. After obtaining the geometric information sequence, search the longest child sequence of the shape to judge the similarity of the combined features, so as to realize the matching of geometric shapes. The geometric shape matching problem is realized by searching LCS of two sequences. The LCS problem is solved by dynamic programming. The relevant function is as follows in equation (3.1).

$$C\left[i,j\right]=\begin{cases} 0,\ \text{when}\ i=0\ or\ j=0 \\ C[i-1,j-1]+1\ \ \text{when}\ i,j>0,x_i=y_i \\ \max C[i,j-1],C[i-1,j],\ \text{when}\ i,j>0,x_i\neq y_j \end{cases} \tag{3.1}$$

In equation 3.1, $C\left[i,j\right]$ serves as the length of LCS; i,j are the serial number;x_i,y_j represent two different sequences of elements. According to the recursive formula, if the element corresponding to the serial number i is equal to the element corresponding to the serial number j , the value of the serial number cell corresponding to the two is written as $c_{i-1}+1$, if the element A is not equal to the element B , the maximum value of $C_{i-1,j}$ and $C_{i,j-1}$ is taken, and so on, and finally LSC is obtained. After GF matching, the annotated object is calculated through iterative comparison of Freeman chain codes, further detecting the text information foundation that needs annotating in the 3DM. The MBD model inspection information includes four points: firstly, product information, such as product attributes, quality, materials, usage, and other basic external features of the design model; The second is basic information, which is separated into two: GF information and appearance feature information; The GF information includes the length, width, thickness, aperture, positioning distance, etc. of the model, while the external feature information includes the shape feature identification, feature category, area, roughness, function, etc. of the model surface; The third is to detect process information, which is used to reflect the product quality level, including design requirements, material information, model geometry information, geometric tolerance information, detection method, positioning information, model roughness, etc; The fourth is to annotate and represent information, usually using different colors to label different detection information to reflect the category of information. The basic information annotation using the MBD model of the front bumper of a car as an example is shown in Fig 3.3.

As shown in Fig 3.3, the specific labeling steps of the automatic labeling method based on Freeman chain codes are to first obtain the Freeman chain codes of the original image and the comparison image, calculate the labeling objects after iterative comparison, and then detect the labeling information in the original image as a comparison The text information basis of the graph annotation, and then use the structural constraints of the geometric feature annotation to map it to the new model to complete the initial automatic annotation. For further enhancing the completeness of annotation, a standard sample dataset was obtained based on the prototype clustering algorithm to inspect and modify the fat bamboo joint tubes, and the annotation results were output. After the annotation is completed, the product is classified. The multi-dimensional nature of product information during classification limits algorithm calculation and inference time. Therefore, Kernel Principal Component Analysis (KPCA) is introduced for dimensionality reduction, and the spatial distribution is shown in Fig 3.4.

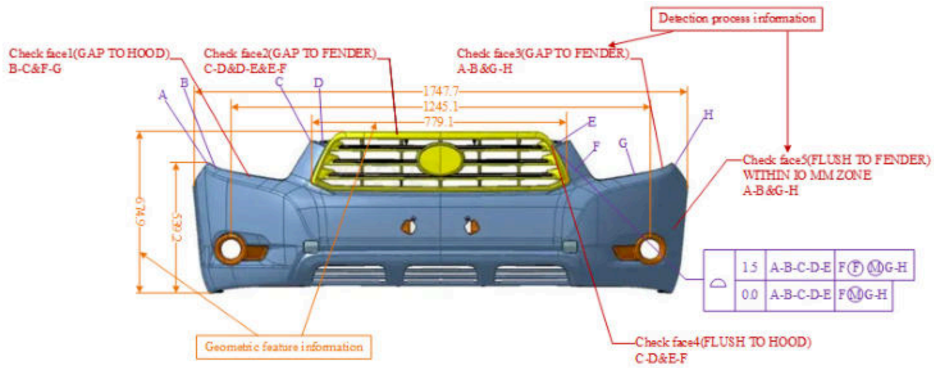


Fig. 3.3: MBD model of the main model of the car front bumper

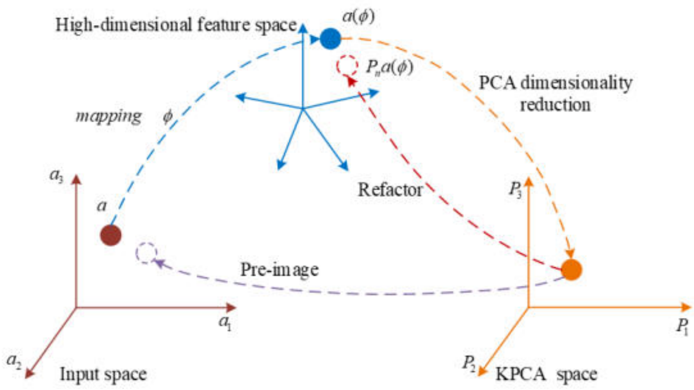


Fig. 3.4: KPCA spatial distribution map

Fig 3.4 indicates that the covariance matrix of the model data $W = W_1, W_2, ...W_d$ is first projected into the determined hyperplane, the sample point of the model generates the image in high-dimensional spatial features through mapping , and the calculation method is shown in equation 3.2.

$$z_i = \phi(a_i), i = 1, 2, ..., m \tag{3.2}$$

Due to the unclear form of mapping , a kernel function is introduced as shown in equation 3.3.

$$k(a_i, a_j) = \phi(a_i)\phi(a_j) \tag{3.3}$$

The eigenvalues and eigenvectors of the covariance matrix are obtained through the kernel function, and the eigenvalues are sorted to obtain the eigenvectors from large to large. By using the PCA algorithm to achieve dimensionality reduction, the $r(r = 1, 2, ..., d')$ -th coordinate of the new sample a after projection can be obtained as shown in equation 3.4.

$$z_r = \sum_{i_1}^{m} h_i^r k(a1, a) \tag{3.4}$$

In equation 3.4,h_i^r is the r-th component of h_i ;k is the kernel function. In summary, the design of a 3DM AAM based on Freeman chain codes and the dimensionality reduction processing of product information have been completed.

3.3. Design of 3D Model Retrieval Method Based on BP NN Algorithm. At present, there are still problems of low efficiency and low accuracy in case retrieval of automotive enterprises, and MBD model retrieval is a key technology to solve this problem. The study utilizes the BP NN algorithm to cluster, classify, and retrieve existing cases for learning, to predict similar MBD models and examine specific structures [19]. BP neural network is a multi-layer feed-forward network trained by error backpropagation, which uses gradient search technology to minimize the mean square error between the actual output value of the network and the expected output value. The clustering of product datasets utilizes the Fuzzy c-means algorithm (FCM) for maximizing the similarity in features of the same cluster and minimize the similarity between features of various clusters, thus classifying samples. The specific principle is to divide the dataset into classes, which correspond to the center points of D classes. If each sample belongs to a certain class$l$, it is u_lb , then the FCM objective function (OF) is depicted in equation 3.5.

$$J = \sum_{l=1}^{N} \sum_{b=1}^{c} u_{lb}^{t} \left\| m_1 - c_b \right\|^2 , 1 \leq t < \infty \tag{3.5}$$

In equation 3.5,t is the membership factor;N is the quantity of samples;C is the quantity of cluster centers (CC); C_b is the l-th CC, with the same dimension as the sample feature; m_1 represents the l-th sample; represents the membership degree of sample to CC C; $\|*\|$ represents a measure of the similarity (distance) of any data, the most common being the Euclidean distance (ED). The constraint conditions are defined to the OF using the Lagrange multiplier method, where is taken as the derivative of U_{lb} and its structure is equal to 0, as shown in equation 3.6.

$$\frac{\delta J}{\delta u_{lb}} = t \left\| m_1 - C_b \right\| u_{lb}^{t-1} + \lambda_b = 0 \tag{3.6}$$

In equation 3.6,λ is the Lagrange multiplier value. Take the derivative of J over d_i and make the result 0, as shown in equation 3.7.

$$\frac{\delta J}{\delta C_b} = \sum_{l=1}^{n} (-u_{lb}^{t} * 2 * (m_1 - c_b)) = 0 \tag{3.7}$$

Finally, the membership matrix is obtained as shown in equation 3.8.

$$\sum_{l=1}^{C} u_{lb} = 1, \forall \ b = 1, ..., n \tag{3.8}$$

The membership matrix representation serves as the degree to which each sample point belongs to each class. For a single sample M_1 , the sum of its membership degrees for each cluster is 1. The closer it is to 1, the higher the membership degree is, and vice versa. The clustering center calculation method is shown in equation 3.9.

$$c_b = \frac{\sum_{l=1}^{N} u_{lb} \bullet m_l}{\sum_{l=1}^{N} u_{lb}^{t}} \tag{3.9}$$

It calculates the CCc_b of each group to minimize the OF (as the OF is relevant to ED, the OF reaches its minimum, the ED is shortest, and the similarity is highest). This makes sure the clustering principle of highest intra group similarity (GS) and lowest inter GS. After the product classification is completed, research is conducted to use the BP network neural algorithm for retrieval learning. The BP network neural algorithm is a multi-layer feedforward NN trained according to the error BP algorithm. By learning the transfer rules, the best output value can be obtained when the input value is [20]. Train with car example (p_e, q_e) , and the mean square error of the case can be obtained from the BP NN as demonstrated in equation 3.10.

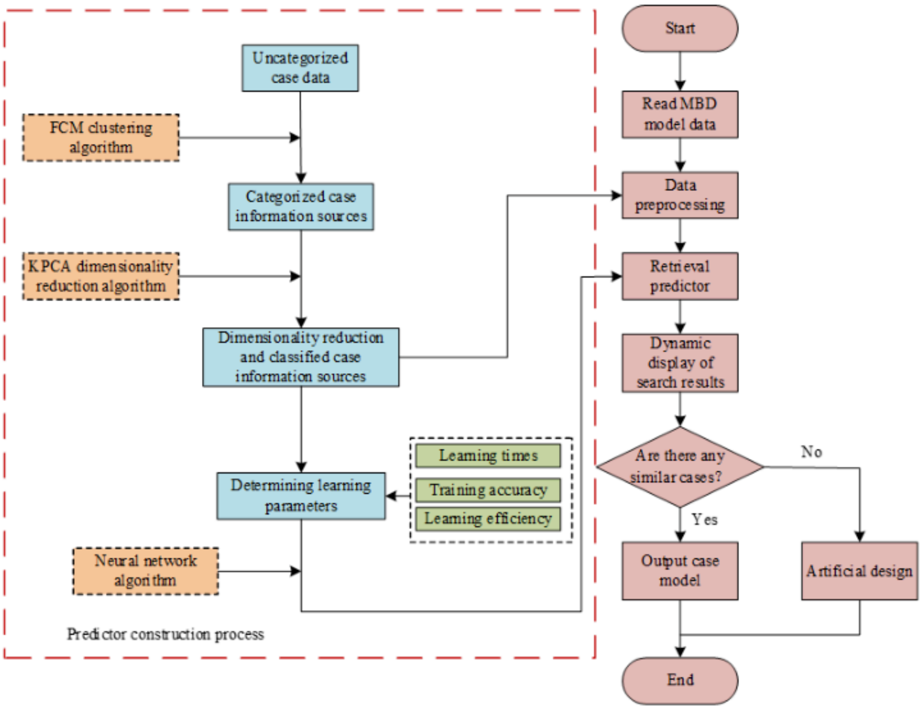


Fig. 3.5: Retrieval process based on BP neural network algorithm

$$E_e = \frac{1}{2}\sum_{e=1}^{s}(\widehat{q}_j^e - q_j^e)^2 \tag{3.10}$$

In equation 3.10,s is the output vector. Then, in the BP algorithm, the gradient descent function is utilized for adjusting from the negative gradient direction, and equation 3.11 can be obtained.

$$\Delta w_{gi} = -\eta \frac{\delta E_k}{\delta w_{gi}} \tag{3.11}$$

In equation 3.11,w_{gi} represents the connection weight in the g-th neuron in the hidden layer and the j-th neuron in the output layer;η is the learning rate. The specific process of the NN algorithm is shown in Fig 3.5.

Fig. 3.5 indicates that the study first extracts MBD model data from the database and preprocesses it using FCM clustering algorithm and KPCA dimensionality reduction algorithm. After determining parameters such as learning frequency, training accuracy, and learning efficiency, the BP NN is utilized for retrieving and predicting the data. Finally, it determines whether the obtained fixture case is similar to the part and outputs the search results. The MBD model retrieval information mainly includes three steps: traversing the MBD model, obtaining model features, and obtaining model main parameters. Due to the wide variety of car models and components, the retrieved cases are prone to local similarity. Therefore, adding a universal and deformable strategy to improve the universality of the inspection tool. Usually, deformation schemes such as settling size chains, replacing skeleton nodes, and replacing skeleton structures are used to design inspection tools. Taking the previous structure of the inspection fixture as an example, the design process of the deformation of the inspection fixture was separated into four steps. The first was to extract the MBD model information and divide the modules, and use assembly constraints to associate each module with the size chain. Finally, it used the main parameters of the parts and assembly to create parameter expressions; The second step is to

(a) Tested geometric model

(b) Similarity check results

Fig. 4.1: Comparison model and result

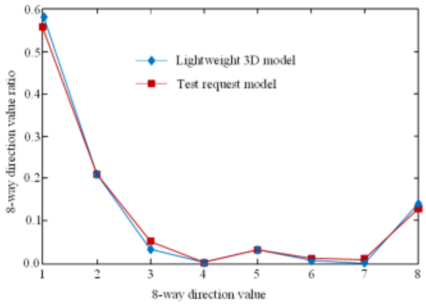
compare the size difference between the retrieved MBD model and the case model, and use the size difference to modify the case fixture structure while changing the main parameters of the simulation block in the chain; The third step is to obtain the main parameters and use the size as the input value to drive the parameter changes accompanying the size, to solve the main parameters of the part; The fourth step is to associate the specific main parameters after solving the size chain parameters, so as to deform the model structure and obtain a new specific structure, while saving the parameters and adding new cases. In summary, the 3DM retrieval method in view of BP NN algorithm and the deformation design of the specific structure for pre inspection were completed.

4. Performance Analysis of Automotive Inspection Tools Based on Freeman Chain Code 3D Model Automatic Annotation Method. As a key tool for inspecting automotive parts, automotive inspection tools possess an essential influence on the automotive production process. For verifying the effectiveness and feasibility of the intelligent vehicle inspection tool design based on the Freeman chain code three-dimensional AAM proposed in the research, this section focuses on testing the similarity of GF and comparing the time consumption of several common annotation methods. Then it further tested the distribution of 7 types of models in 2D and 3D spaces, as well as the structural dimensions of the product after deformation.

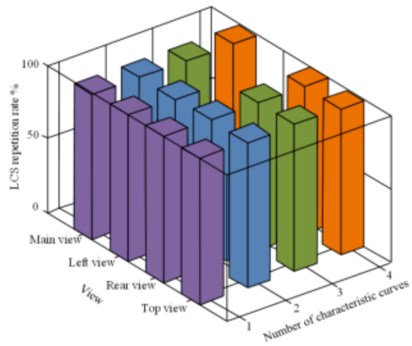
4.1. Performance Analysis of 3DM Automatic Annotation Method Based on Freeman Chain Code. For verifying the effectiveness of the AAM for 3DM in view of Freeman chain codes, 12 sets of GF were input. This is to test the maximum number of sub sequences and repetition rate between the GF of the detection task book and the GF of the 3DM.

Fig 4.1a shows 12 sets of GF tested; Fig 4.1b shows the similarity test results. The test indicates that the accuracy of using LCS to search for GF matching of each group of data is relatively high, and there is a significant difference in feature comparison results. This proves that using LCS to solve geometric shape matching problems is practical and feasible. To explore the feasibility of automatic annotation of 3DM based on Freeman chain codes, research was conducted on automatic annotation of 3DM of car front bumpers, the 8-channel eigenvalue of the geometric model is selected as the evaluation index, and the 8-channel eigenvalue refers to the similarity of the 8 prominent features of the geometric model.

Fig 4.2a shows the comparison chart of the eight channel values of the two geometric modeling. The results show that the eight channel values of the two geometric modeling are approximately equal, indicating that the two geometric characteristics are similar. Fig 4.2b illustrates the LCS comparison of the characteristic curves of various views of the front bumper parts. The LCS size of the two geometric modeling shows that the geometric characteristics of the two models are similar, and the LCS repetition rate shows that the lightweight model can fully label the selected objects, which further proves that the method can complete the automatic annotation of the model. The study selected 8 surfaces and used geometric similarity annotation, traditional manual annotation, 3D cube annotation, 3D radar point cloud annotation, and 3D automatic annotation to



(a) Comparison chart of the proportion of 8-way direction value of two comparison model



(b) The LCS comparison results of the characteristics curves of each view of the bumper parts

Fig. 4.2: The comparison results of the 8-pass value ratio and the characteristic curve LCS of the two comparison models

Table 4.1: Completeness and time-consuming comparison of several model annotations

Marking method	Color	Object	Structure	Benchmark	Surface	Time consuming/min
Geometric similarity annotation	87.89%	100%	100%	100%	62.5%	3
Traditional manual labeling	67.83%	75.25%	83.63%	89.86%	50.25%	10
3D cube annotation	85.79%	83.81%	86.05%	80.74%	51.35%	8
3D radar point cloud labeling	78.36%	81.82%	84.23%	85.87%	56.48%	6
3D automatic annotation	77.34%	79.97%	83.56%	92.57%	52.39%	5

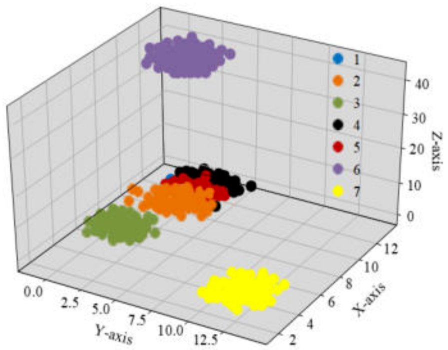
detect the completeness and time-consuming of corresponding surface annotations.

Table 4.1 shows the completeness and time consumption comparison of eight surface annotations by several models. Compared to traditional manual annotation and other annotation methods, the AAM in view of GF similarity achieves 100% accuracy in annotation structure, objects, and benchmarks, and only takes 3 minutes to complete the annotation, which is 7 minutes longer than traditional manual annotation. The results show that the geometric similarity annotation method can greatly reduce annotation time, improve the accuracy of annotation results, address the issue of easy annotation errors, and meet the detection requirements.

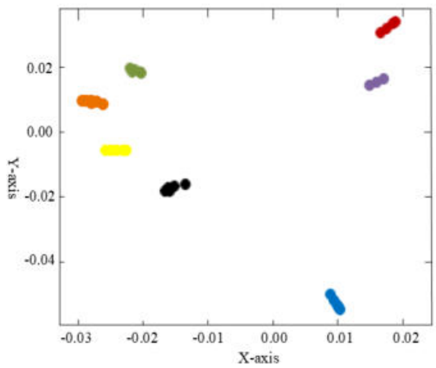
4.2. Performance Analysis of 3D Model Retrieval Technology Based on BP NN Algorithm. To verify the feasibility of 3DM retrieval technology based on BP NN algorithm, the study divided car models into 7 categories, utilized KPCA for dimensionality reduction, and tested the distribution of the seven types of models in 3D and 2D spaces. It is showcased in Fig 4.3.

Fig 4.3a shows the three-dimensional spatial distribution of relevant model data; Fig 4.3b shows the two-dimensional distribution of relevant model data after dimensionality reduction using KPCA. Most of the 7 features are not significantly separated in 3D space, and after using KPCA dimensionality reduction processing, the 7 features are completely separated and clearly distinguished. This proves that KPCA can effectively distinguish GF, accelerate the speed of GF classification, and reduce model retrieval time. This study further utilizes the FCM clustering algorithm to process seven types of model data and test the data classification performance.

Fig 4.4 indicates the clustering of the FCM algorithm. The clustering illustrates that the FCM algorithm can effectively serve as the clustering centers and ranges of each type of GF, accurately achieve feature classification results, and reduce the complexity of retrieval. For verifying the feasibility of retrieving deformation design in



(a) Comparison chart of the proportion of 8-way direction value of two comparison model



(b) The LCS comparison results of the characteristics curves of each view of the bumper parts

Fig. 4.3: The comparison results of the 8-pass value ratio and the characteristic curve LCS of the two comparison models

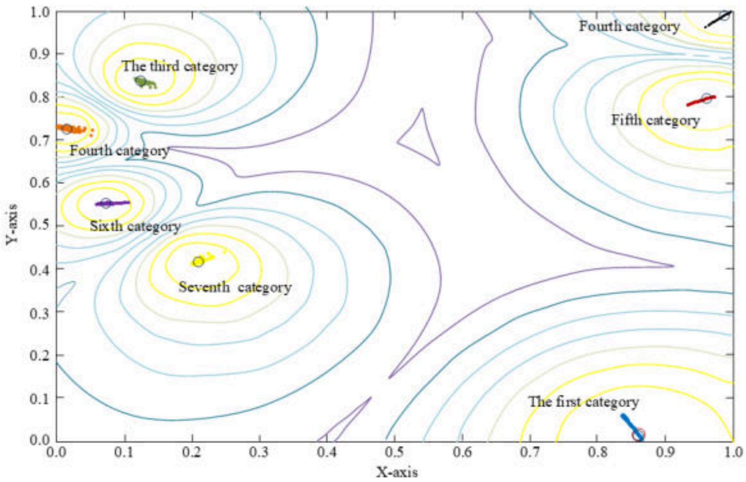
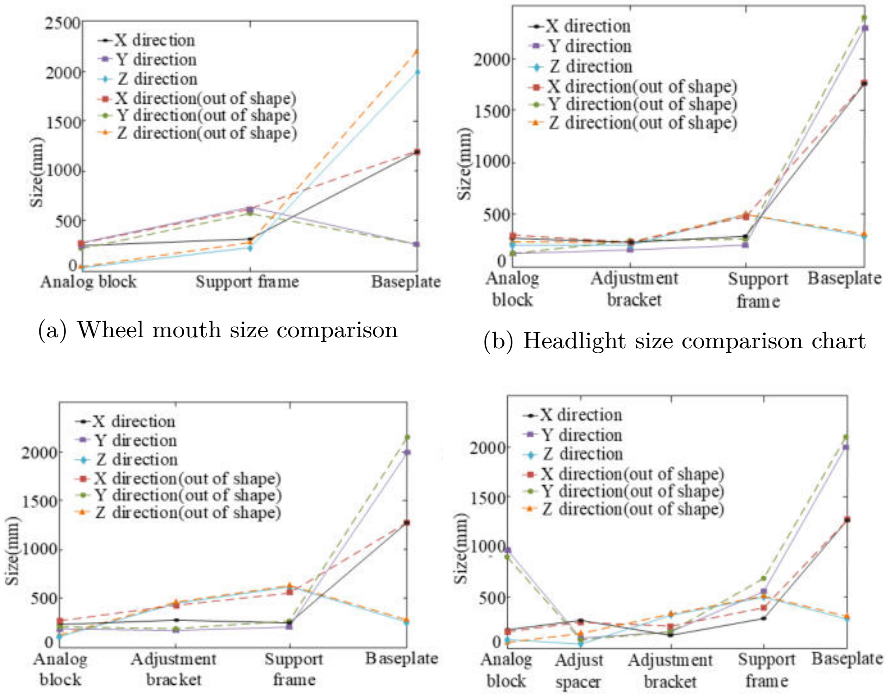


Fig. 4.4: FCM algorithm clustering results

automotive inspection fixture design, this study takes the front bumper model of an automobile as a case to perform similarity retrieval and adjust each dimension chain based on existing cases. The deformation design is completed by modifying the main parameters, and the structural dimensions of the product after deformation are tested.

Figs 4.5a to 4.5d show a comparison of the dimensions of the wheel opening module, headlight module, fender module, and hood module, respectively. The comparison results show that the deformation design solutions of the four modules do not conflict in size and have a high utilization rate, without any abnormalities, and can successfully complete structural deformation. It further verifies the efficiency of solving the deformation of dimension chain design gauges, and records the design time required for wheel openings, headlights, fenders, and hood under the conditions of manual model gauges, high similarity model gauges, medium similarity model



(a) Wheel mouth size comparison

(b) Headlight size comparison chart

(c) Fender size comparison chart

(d) Hood size comparison chart

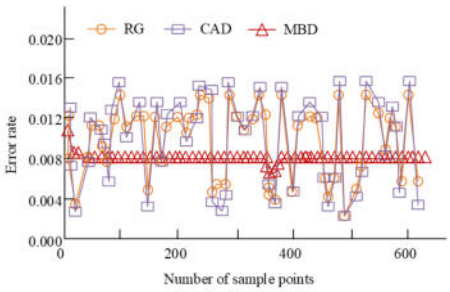
Fig. 4.5: Three-dimensional space and two-dimensional space distribution diagram of seven types of model data

Table 4.2: Design time comparison chart

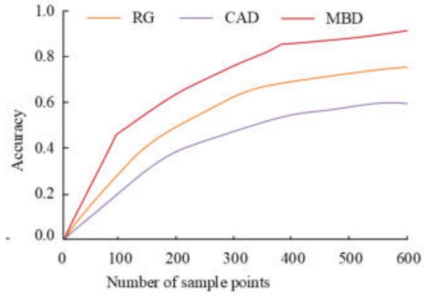
Marking method	Color	Object	Structure	Benchmark	Surface	Time consuming/min
Geometric similarity annotation	87.89%	100%	100%	100%	62.5%	3
Traditional manual labeling	67.83%	75.25%	83.63%	89.86%	50.25%	10
3D cube annotation	85.79%	83.81%	86.05%	80.74%	51.35%	8
3D radar point cloud labeling	78.36%	81.82%	84.23%	85.87%	56.48%	6
3D automatic annotation	77.34%	79.97%	83.56%	92.57%	52.39%	5

gauges, and low similarity model gauges.

Table 4.2 shows the required design time for wheel openings, headlights, fenders, and hood. The outcomes showed that relative to manual reverse deformation design, the design time of model inspection tools with higher similarity in size chain deformation design was reduced by 214 minutes; And the design time of each module is significantly reduced, and the design efficiency is significantly improved. In summary, the intelligent vehicle inspection tool proposed by the research institute based on the Freeman chain code for 3DM AAM significantly improves the retrieval accuracy and greatly reduces the retrieval process by using KCPA dimensionality reduction, FCM algorithm classification, and integrating BP NN algorithm for retrieval. Its successful application and design optimization of similar cases. In order to verify the effectiveness of the automobile inspection tools proposed in the research, the study uses the proposed automatic marking method of 3D models based on Freeman chain codes for intelligent automobile inspection tools, and the automobile inspection tools based on computer aided drafting (CAD) platform. Automobile gauge based on relational graph (RG) is tested on the same vehicle model, and the detection error rate and correct rate are selected as performance evaluation



(a) The detection error rate of the three kinds gages



(b) Accuracy

Fig. 4.6: Detection error rate and precision rate of three kinds of gages

indicators.

Figure 4.6a and Figure 4.6b respectively show the error rate and accuracy rate of the three kinds of inspection tools for the detection of car models. The results show that the inspection tool of the research institute performs better in terms of error rate and accuracy rate, the detection error is the smallest and the fluctuation range is not large, which has good advantages. The highest accuracy rate of the proposed gage is 93.56%, the accuracy rate of RG is 91.34%, and the average accuracy rate of CAD is 90.22%. To sum up, in the process of gage design, the automatic labeling method based on Freeman chain code is used to mark the case structure and information, the BP neural network algorithm is used to classify the case information, and the FCM and KPCA algorithms are used to optimize the information source. The proposed intelligent checking fixture can improve the retrieval efficiency of similar cases, shorten the development cycle of new products, improve the design efficiency of new products, and lay a foundation for the intelligent design of checking fixtures.

5. Conclusion. Automobile inspection fixture is an important tool for automobile research and development, which affects the automobile research and development process and the manufacturing accuracy of the whole vehicle. For enhancing the design of automotive inspection tools, this study presented an intelligent automotive inspection tool design method based on Freeman chain code for 3DM automatic annotation. The results showed that the GF matching accuracy of the 12 sets of data searched using Freeman chain codes and LCS was high, and the difference in feature comparison results was significant. Compared with other annotation methods, the geometric similarity annotation method has a 100% accuracy in annotating structures, objects, and benchmarks, and only takes 3 minutes to complete the annotation, which is 7 minutes longer than traditional manual annotation. The test results demonstrate that the GF are completely separated and clearly distinguished after using KPCA dimensionality reduction processing, and the FCM algorithm can accurately achieve feature classification. For the deformation design of wheel openings, headlights, fenders, and engine hood, the dimensions of the dimension chain inspection tool are not conflicting and have a high utilization rate, without any abnormalities; The required design time was reduced by 214 minutes compared to the manual reverse deformation design, and the design efficiency was significantly improved. Compared with RG-based gages and CAD-based gages, the error rate of the gages proposed by the research institute is the smallest, and the highest accuracy rate is 93.56%. To sum up, the intelligent automobile gage proposed by the research institute can improve the efficiency of automobile design, realize the intelligent design of the gage structure, and provide reference value for the intelligent development of gage design. However, there are still shortcomings in the research, with a focus on completing the intelligent design of inspection tools. Further research can improve and deepen the optimization of retrieval structure, design methods, and model retrieval information sources.

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